Examining the Relationship between Cognition and Response Behavior in Health Retirement Survey

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Abstract

This paper examines the answering behavior of the old respondents. There is a growing interest in the cognitive decline of the aging population, but not enough is known about the consequences and implications of cognitive decline or its manageability from public policies outside the medical literature. The major challenge is insufficient measures of one's cognition even in popular surveys such as Consumer Expenditure Survey. The objective of the paper is to create the individual proxy from each respondent's answering behavior in the survey data. Note that taking a survey requires a series of cognitive tasks. Respondents need to comprehend the question, search their memory, make a decision, and format the response to a given scale. This paper proposes a standardized measure of answering behavior using open-ended financial questions in the Health and Retirement Study. I estimate the proxy of one's cognitive ability based on one's answering behavior and try to make it comparable. The measures are in line with the respondents cognitive score in the HRS.

JEL classifications:

Keywords:

*Updated soon

1 Introduction

Cognitive decline refers to the difficulty with the process of using the brain functions to consider something. It could occur gradually or suddenly, and it could be temporary or persistent. The fact is that cognitive decline is one of the most common conditions among the elderly. According to the public health issue report from the Center for Disease Control and Prevention, every one in nine adults is reporting experiences of cognitive decline. The incidence prevalence is 10.8 percent among adults 45–64 years old and 11.7 percent among adults aged 65 years and older. It is becoming a public concern given that about 30 percent of adults experiencing cognitive decline live alone. The seniors who live by themselves could be more susceptible to poor health outcomes than those living with others (Gibson and Richardson 2017; Portacolone et al. 2018). Also, it is one of the earliest noticeable symptoms of Alzheimer's disease and related dementia (Jessen et al. 2014). Since cognitive decline, also known as cognitive impairment, would entail considerable medical and social costs, research in cognitive decline is associated with the economics of aging and health. Economists in many areas contribute to an understanding of the issues related to cognitive decline and help the design of public programs (Chandra, Coile, and Mommaerts, forthcoming). The problem is that there is a limited number of data or surveys, which include cognitive assessments with respondents' demographics. This lack of data availability hinders researchers' ability to examine questions of high policy importance.

In this paper, I create the indices as a proxy for individual cognition based on the pattern of the survey responses. I assume that a person experiencing cognitive impairment could lose precision in numbers, so provide fewer significant figures when answering open-ended financial questions or skip the questions more often than general respondents. I particularly examine the open-ended financial questions for the following reasons. First, the financial questions are available in popular survey-type microdata such as the Panel Study of Income Dynamics. Second, the literature finds that the financial responses on the survey data show more heaping patterns compared to the administrative data, and it implies that answering the financial questions demands advanced mental operations (Riddles et al. 2017).

For this project, I use the Health and Retirement Study (HRS), a nationally representative longitudinal survey. The HRS provides extensive longitudinal data on the U.S. elderly with a range of health and financial information. Some questions are directly related to the respondents' memory and cognitive ability, and hence the constructed cognitive proxies can be tested. For constructing the proxies, it is important to ask how to select the financial questions, how to measure the rounding behavior of the response, and how to deal with opt-out options. I select the financial questions based on the response rate because the low response rate would mean that the question is of little value to consider. I measure the rounding behavior based on Gideon, Helppie-McFall, and Hsu (2017) and provide the alternative. Given that the survey questionnaires often provide opt-out options such as selecting *do not know* or skipping the question, I try to incorporate this behavior.

I find the following results from my empirical analysis on the proxies. First, most proxies become progressively worse with age. The most significant changes in cognition with aging would be depreciation in performance on cognitive tasks (Murman 2015), and my proxies capture this pattern. That is, the older individual is more likely to round the responses and choose opt-out options. Second, the proxies are sensitive to how to measure the rounding behavior, but in general, incorporating opt-outs dramatically improves the fit to capture the age pattern of cognition.

The proxies have some advantages over the traditional proxies, such as the years of schooling or age. The level of education would have predictive power on one's cognition. However, it does not capture the aging trend of cognitive ability, since the years of schooling rarely changes among the elderly. Using age as a proxy for cognition captures the linear age trend, because age certainly changes as time goes by. However, it implies that the marginal effect of time on the cognitive ability is the same for everyone, which is too strong assumption to be employed. My proxies not only present the aging trend but also generate meaningful distribution. I further examine the correlation between our proxies, cognitive score in the HRS, and other demographic variables to see whether it closely matches the previous findings. Eventually, I want to apply the method to other survey data that do not have any measurements of cognition, and therefore give a guideline of making a cognitive proxy for the researchers who want to study the cognition but do not have it in their data set.

As an application of the project, I employ the Panel Study of Income Dynamics (PSID). The PSID includes a similar set of open-ended financial questions with more detailed individual episodes.

describe what I did...

2 Literature Review

I examine the survey response from the HRS and find evidence of rounding. I specifically find that the rounding (or skipping) pattern would be systematically observed across respondents and hypothesize that the pattern is associated with cognitive ability. Rounding or digit preference, also known as response heaping, is frequently observed in interview-administered surveys. Uncertainty about the true response is a common problem when researchers analyze such a numerical question. There is widespread support for taking numerical responses at face value, but many researchers try to estimate the degree of heaping in data and develop techniques to handle resulting problems such as attenuation bias (Manski and Molinari 2010; Roberts and Brewer 2001; Zinn and Würbach 2016). Riddles et al. (2017) empirically show that the responses to the financial questions are unlikely to reflect the true value, and I examine further whether those differentials would systematically capture one's cognitive ability. Furthermore, I examine the extent to which the findings from the HRS can be applicable to other settings.

The empirical investigation of the extent to which the survey response would predict the respondent's cognitive ability contributes to several distinct literature. The first related body of work analyzes the survey completion of the entire survey (Krosnick 1991). A set of papers explore the proportion of the skipping pattern and study the reasoning behind the opt-out behaviors. Many surveys offer the respondents explicit optout options such as *don't know* or *refused to answer*. Colsher and Wallace (1989) show that the old respondents are more likely to choose opt-outs. Their findings explain that opt-out answers are considered as taking cognitive shortcuts to make question answering easier and that this pattern partly captures the cognitive decline. Knäuper et al. (1997) specifically study how often the respondents aged 70 years old and older choose *don't know* and find that the respondents with low cognitive ability tend to choose this option more on difficult questions. Another set of paper examine the relationship between the cognitive ability and the numerical response directly. Holbrook et al. (2014) focus on the specific digit preference. Gideon, Helppie-McFall, and Hsu (2017) examine the rounding behavior in a broader manner. They study intraclass variation of the respondent's rounding behavior. Andrews and Herzog (1986) examine the relationship between the variance of the numerical responses and the respondent's age.

describe psid application

3 Data Description for the HRS

I use the 2004 to 2018 waves of Health and Retirement Study. The data covers the U.S. residents aged 50–89 years old in the survey periods. I have information about a set of demographic variables such as gender and age, educational attainment, financial portfolios, health status, and date of completion. A unique person and family identifier allow me to follow the corresponding respondent over time. I use the 2004 survey as the starting wave because it is the first year in which the baby boomer generation is added. Some questions target on the household level response, and the HRS indicates the individual respondent either as the financial respondent, family respondent, or coverscreen respondent (the first respondent interviewed) on behalf of the entire household. In most cases, one family member answers the household-level questions. If the roles are separated among the family members, I mainly focus on the individual responding to the financial questions because the interest lies in the open-ended financial questions. I ignore if the main respondent is either sibling, child, or helper.

As a result, pooling 16,187 individuals across the seven waves, we construct a sample of 62,851 individual-years. Table 1 presents the parsimonious summary statistics of the data. The overall demographic does not change by the survey year except for the mode of the interview. The respondents are more female and completed high-school education on average. Many respondents encounter different modes of interviews during the periods. Before 2002, the HRS is surveyed through face-to-face interviews at baseline, and the telephone is used for follow-up interviews. The selection issue on the interview mode is less concerned since after 2006, half of the core sample is randomly assigned to face-to-face, and the rest is assigned to telephone interviews.

3.1 Cognitive score

The HRS has a series of tests on one's cognitive ability. The questions are related to episodic memory, mental status, and comprehension of vocabulary, and each correct answer scores numerical points. I define the overall cognitive score as the sum of the three questions *immediate word recall*, *delayed word recall*, and *serial 7's test* and use it as a reference index of the cognitive ability[1]. For the immediate word recall, the respondents observe the ten-noun list, and then they are asked to recall the list in order. A few minutes later, the respondents are asked to recall the same list of the words again. This is the delayed word recall. For the serial 7's test, the respondents are asked to subtract 7 from 100, and continue subtracting 7 from the last response. The respondents are asked to try this five times. The score range of the immediate word recall and delayed word recalls are both zero and ten, and the serial 7's test is between zero and five. Therefore, the cognitive score ranges from zero to twenty-five.

Figure1 plot the average score of the cognitive questions in the HRS against age in years. All the plots show a similar aging trend. There is little variation until age 65, but sharp declines are observed after 65. There is no consensus on when the cognitive decline starts in medical literature, but there is a general agreement that the cognitive decline would be accelerated for the old people (Karr et al. 2018). Hence, I sample the respondents aged between 65 and 90 and use the cognitive score as a benchmark.

3.2 Question selection

The HRS contains a range of financial questions[2]. I select the questions based on the following criteria. First, I pick up the open-ended response format questions. It rules out any closed-ended questions. Second, I drop the time-related questions. Then, I keep the questions based on the response rate. This is mainly because many questions are applicable to only a few respondents, so the representativeness is in question. Lastly, I check whether the selected questions appear in every wave. The ten questions meet the criteria: *the present value of home, real estate taxes, social security income, checking account, transportation value, food at home, food away from home, out-of-*

1. Herzog and Wallace (1997) claim that the selected questions are relevant to verbal learning, reasoning, and attention abilities, essential to the cognitive skills.

2. Financial questions mainly belong to the following sections: health care cost (N), family structure (E), housing (H), asset and income (Q), capital gains (R), job (J, L), disability (M), insurance (N), and divorce (S).

pocket for doctor visit, dental bills and *drug costs*. Figure 2 presents the average numerical response by age for each question. One common characteristic among the ten questions is the strong patterns of heaping on round numbers (or digit preference)[3].

Table 2 presents the summary statistics for the ten questions. I believe that a massive variance in numerical response and high opt-out rates would provide enough variation to construct proxies. I exclude the eat-out expense question because more than 40 percent of the response is a single digit. That is, there are no trailing zeros for a single-digit response. Also, I exclude home and vehicle value questions. The numerical answers to these questions are based on the respondent's judgment and memory, and the transactions occur far less frequently than other items. Therefore, it is unlikely that the respondents provide meaningful responses compared to the everyday expense. I leave the analysis in these questions for the later section.

3.3 Demographic variables

Demographic variables include age, mode of interview[4], gender, years of schooling, and wealth. These are important along with the cognitive score to test our proxies are consistent with previous findings. We define total wealth as the sum of nonfinancial wealth, retirement wealth, and other financial wealth. Since the values are nominal, we first deflate the values using the price index in 2012 for Gross Domestic Product from the National Income and Product Accounts. The years of schooling does not change by time. It is possible that the respondents gain more schooling between the survey years. However, only four respondents in our sample gain more years of schooling. Race and where the residents live are probably important factors, but these are restricted information in the HRS.

4 Characterizing Response Behavior

In this section, we characterize the respondents' answering behavior. Although open-ended questions cannot be answered with a statistic response such as "yes" or "no", the HRS provides respondents

3. See Figure 3.
4. The mode of interview indicates whether a respondent is interviewed by either face-to-face or phone.

the opt-out options "don't know" and "refused to answer". Hence, characterizing the behavior takes account the degree of details on numerical responses and whether the one chooses opt-outs. We start with measuring the degree of details for each question and consider how to add opt-out response subsequently.

4.1 Measuring the degree of details

We count the number of non-trailing zeros and the total number digits for each numerical response, and then create the index of the degree of details. We introduce two ways of creating the index which look similar but present subtle differences. We define m as the total number digits and n as the number of non-trailing zeros. The first index is following Gideon, Helppie-McFall, and Hsu (2017), in which the index is calculated by $\frac{n-1}{m-1}$[5]. The second index is calculated by $\frac{n}{m}$. 1 is the least upper bound for both indexes, and the larger value means the more detailed response.

There are two differences. Consider two responses \$1,000 and \$10,000,000. Following the above notation, n is equal to 1 for both responses, m is equal to 4 and 8 respectively. So, the firsts index calculates both responses as zero. Gideon et al. label this type of responses as *maximal rounding*. On the other hand, following the second index results in 0.25 and 0.125, and therefore the latter response is regarded as less detailed. That is, the scale of response matters for the second index especially when the respondents do maximal rounding. The second difference is the range of the index. Although both measures use the fractions less than or equal to one, $\frac{n}{m}$ does not include zero in the range since n never be zero for numerical responses.

There are two findings presented in both indexes. First, although the range of the fractions could be large, but the certain fractions are much more observed than others. Figure **??** presents the distributions of the first index among the selected questions. The significant mass is observed on zero, maximal rounding, in most questions. The similar patterns are observed in the second index[6]. Although the distribution looks more spread, only a few fractions have the observations. The second finding is that the large number bias would not be a concern. Some might argue that one would

5. The original method by Gideon et al. is $\frac{m-n}{m-1}$. We transform its direction using $1 - \frac{m-n}{m-1}$ to make two measures are comparable in direction.

6. See appendix Figure **??**.

respond with more trailing zeros if the magnitude of the response is larger. Figure **??** presents the local average of numerical response by $\frac{n-1}{m-1}$ the first index. If there were large number bias, the negative relationship would be expected. However, Figure **??** shows no linear patterns. The second index presents the similar result.

4.2 Constructing Proxy

The HRS offers opt-outs in most questionnaires. The response rate of opt-outs in the HRS is quite high (Table **??**)). Ideally, the proxy should reflect the varying degree of details on numerical responses. At the same time, it would be better if the proxy can capture whether the respondents choose opt-outs, because too many respondents often choose it. We build the proxies based on the two index we constructed above. In the rest of paper, we discuss seven proxies constructed in the following manner. We define proxy 1 as the average of the first index for the selected questions, and proxy 2 as the average of the second index for the same set of questions. That is, proxy 1 and proxy 2 only deal with the degree of details on numerical questions. The rest of proxies explicitly take account the opt-out option. To construct proxy 3, we calculate the index $\frac{n-1}{m-1}$ for each question. If the respondent answers DK, we assign 0 to the index. Proxy 3 takes the average of them. Proxy 4 is similar to proxy 3 but uses the index $\frac{n}{m}$. The interpretation between proxy 3 and proxy 4 has a subtle difference. Proxy 3 treats DK as the same as the maximal rounding. On the other hand, in proxy 4 DK means that the respondent answers with the less detailed degree compared to any numerical answer.

Note again that certain fractions are much more observed in Figure **??** in the first index. It raises the concern on proxy 3 and proxy 4 because the most variation in the proxies might come from whether one chooses the opt-out or not. To test this concern, proxy 5 and proxy 6 focus on whether the respondent do maximal rounding. To construct proxy 5, for each question, we construct the index in the following way. 0 is assigned to DK, 1 is assigned to maximal rounding, and 2 is assigned to any other numerical values. Proxy 5 takes the average of them. To construct proxy 6, we assign zero to either DK or maximal rounding, and one to any other numerical responses for each question. Proxy 6 takes the average of them. It is possible that the useful variation only comes from whether the respondents choose opt-outs or not. Proxy 7 tests this claim. For each question we assign zero to

DK and one to any numerical response, and then take the average of them.

5 Proxy Evaluation

In this section, we evaluate the proxies based on the two aspects. Note that Figure **??** shows the average cognitive score declines as age increases. The minimum condition of the proxy is whether it can capture the aging pattern for the respondents ages 65 and older. Interestingly, HRS has a panel dimension so that we can further examine whether the individual over-time pattern of proxies match the corresponding cognitive score. Secondly, we assess the correlation between the proxies and demographic variables to check whether the results are consistent with the previous literature findings. Each proxy is based on the distinct counting method. From the regression exercise, we can also examine whether the results are sensitive to the counting methods. Since the range of cognitive score and proxies are different, we standardize the cognitive score and all proxies.

5.1 Local average of Proxies by age

Figure 6 presents the local average of proxies by age. The cognitive score in the first panel serves as a benchmark. Note that the proxy 7 only deals with whether the respondents choose opt-outs or not. It is quite simple but presents the consistent pattern with the cognitive score according to the last panel. Then, the question is whether incorporating rounding behavior provides a marginal value to predict the cognitive ability. Also, given that many surveys do not provide explicit opt-out options, how much proxy 1 and proxy 2, which takes account the rounding behavior only, provides the information on cognitive ability should be assessed. All proxies except proxy 1 and 2 seem to capture the age pattern of cognitive score closely. Proxy 1 and proxy 2 show the decreasing trend with high variance.

Since the HRS is a panel data, we can examine the proxy pattern within the same person by controlling for the individual fixed effects. Figure 7 presents the local average by age, and the first panel serves as a benchmark again. All the panels have the negative trends, and even the proxy 1 and 2 correspond to the pattern of the cognitive score. Note that in both figures proxy 3, 4, 5 and 6 show very similar patterns compared to the pattern of the cognitive score. It might imply that the resulting patterns are not sensitive on how to incorporate opt-outs. On average, we find that respondent not only rounds more but also opts out more as they get older. Taking account rounding behavior only would estimate the cognitive ability poorly for the cross-sectional data. However, in the panel data proxy 1 and proxy 2 would be a good proxy for the cognitive ability[7].

5.2 Empirical Analysis

The empirical framework models the extent to which answering behavior varies with the characteristics of the respondents. In the regression analyses, we try to find correlations and associations among variables that could be helpful in understanding the respondents' answering behavior. We test all proxies and examine the partial correlation between each proxy and demographic variables. Again, the HRS has the cognitive score so that we can examine whether our results match the previous findings in literature, and therefore we might have a partial justification for our proxies. Of course, we acknowledge that the estimation risks omitted variable bias, but we mitigate this concern in part by providing ample robustness checks. In this section, we test whether response heaping is more observed among the low-income respondents (**myers1976instance**). Using the years of schooling, we examine the claim that illiterate respondents present more response heaping (**budd1991intentional**). Lastly, we test whether female rounds more as in **boyle1986fertility**. All the previous findings are based on the cross-individual analysis. We examine which proxies are consistent with the literature and further explore whether the results are changed in the individual fixed effect models.

We estimate several variants of the following linear regression model for the respondent i at time t,

$$Proxy^j_{i,t} = \alpha^j_i + \beta^j_1 age_{i,t} + \beta^j_2 Interview\ mode_{i,t} + \beta^j_3 wealth_{i,t} + \beta^j_4 cognition_{i,t} + X_{i,t}\gamma + \epsilon^j_{i,t} \tag{1}$$

where $j = \{1, 2, 3, 4, 5, 6, 7\}$. i and t indicate the survey respondent i and survey year t. j denotes the classification of the proxy. age is the respondent's age, $Interview\ mode$ indicates the method of survey[8], $wealth$ is wealth quantile of total wealth, and $cognition$ is the cognitive score in the HRS.

7. It would raise the questions on whether the results depend on the question selection. We discuss it in the robustness-check section.

8. It is a binary variable. The value one indicates the phone interview, and zero indicates face-to-face interview.

$X_{i,t}$ is a covariate vector including gender and years of schooling. So far, we examine relatively parsimonious specifications with very limited number of demographic variables. Gender and years of schooling do not change over time within the same individual, and hence in the individual fixed effect model, γ is not identified. β_1^j, β_2^j, β_3^j, and β_4^j are parameters to be estimated. In most surveys, variables on cognition are not available, but we add it into the model because the partial correlation between the proxies and cognition in part determines their justification for usage.

The age effect is captured by a continuous age variable. Since the respondent's answering behavior is a function of age, controlling for age effect is important in order for other parameters to capture the net effect on the behavior. The mode of interview is included to account for difference in answering attitudes. The wealth quantile is included to examine whether the pattern of answering behavior is different based on economic conditions. We expect the estimate of β_1 to be negative and significantly different from zero, while the estimate of β_2 to be much smaller in magnitude or statistically insignificant. The estimates of β_3 and β_4 are expected to be positive.

Table **??** presents coefficient estimates for the equation (1) without the individual fixed effects. Each column shows the resulting coefficients using the proxy as a dependent variable. Note that the sign of the coefficients on age, cognitive score, and mode of interview are very similar among the proxies. On average, the respondents more likely round the number (or choose opt-outs) when the respondents are older controlling for cognition and other demographic variables. Similarly, controlling for age and other variables, the respondents on average less likely round the number (or less likely chooses opt-outs) when they have higher cognitive ability.

Note that there is no conclusive result on the effect of gender, years of schooling, and wealth. The sign and magnitudes of coefficients on education, female and wealth differ even among proxy 4, 5, 6 and 7 in contrast to Figure 6 in which proxy 4, 5, 6 and 7 present similar patterns. **boyle1986fertility** find that women present more response heaping than men, but the consistent results are only found in proxy 5 and proxy 7. Also, **budd1991intentional** show that response heaping is more frequently observed among illiterate respondents, and hence the sign of education might be a concern for all proxies except proxy 6 although the correlation between the years of schooling and illiteracy is somewhat vague. Lastly, **myers1976instance** finds that the low-income respondents more likely show response heaping, but the results are incompatible among the first four proxies in our regression.

There are two takeaways from the cross individual analysis. First, the regression results are sensitive to the counting methods. Note that we use two similar methods measuring the rounding behavior for each question. Proxy 1 is based on $\frac{n-1}{m-1}$, and proxy 2 is based on $\frac{n}{m}$. They look similar but have different inference on maximal rounding. The column (1) and (2) present that the resulting coefficients have different magnitudes and signs. Secondly, the regression results are sensitive to how to incorporate the opt-outs. We implicitly make two separate assumptions to add opt-outs to the proxy. First assumption is that DK means more rounding than maximal rounding. This assumption is applied to proxy 4, and proxy 5. The second assumption is that answering DK and maximal rounding are considered the same. Proxy 3 and proxy 6 are based on this assumption. Especially, the only difference between proxy 5 and proxy 6 is how to handle the maximal rounding. Column (5) and (6) show the results on proxy 5 and 6 and present that the resulting coefficients have different magnitudes and signs. The regression results from the cross individual analysis might indicate that using a single proxy is not enough to estimate the cognition. However, as in Figure 6, each proxy could provide meaningful information on the cognitive ability, and hence combining proxies might be necessary to estimate one's cognition for the cross individual data. We test this by running the regression of the cognitive score on proxies in Table **??**. The column (1) and column (2) only contains the single proxy. The column (3) includes multiple proxies and show the cognitive score is better explained compared to the single proxy model. In fact, the proxy selection is the result of Lasso adaptive model. We only test 7 proxies along with the demographic variables. We leave the complete model selection by Lasso for future works.

Table **??** presents the coefficient estimates for the equation (1) with the individual fixed effects. On average, controlling for the change in cognitive score and other demographic variables, the respondents are rounding more (or opt out more) as they get older. As in Figure 7, controlling individual fixed effects improves fits dramatically. Among proxy 3, 4, 5, 6 and 7, all the signs of the coefficients are the same, and the magnitudes are also similar. Even proxy 1 and proxy 2 present the similar estimates except wealth. Compared to the cross-individual analysis, in the panel data, either counting methods or how to incorporate opt-outs would not affect the estimation much. Also, given the variation in proxies are largely explained by the variation in cognitive ability, each proxy can be a good estimate of the respondent's cognition in panel data.

Note that gender do not change within the same person over time, and hence it is omitted in the fixed effect models. Note also that two groups are hardly comparable as the number of observations denotes. The size of female households grows more and more as the respondents get old. In appendix[9], we present the individual fixed effects model by gender. We do not find meaningfully different implications compared to Table **??**.

5.3 Robustness check

Note that the cross individual analysis is sensitive to counting methods and how to incorporate opt-out responses, and hence in this subsection, we perform the robustness checks on the individual fixed effect models only.

We use 7 questions and take the average of the responses according to the construction method for each proxy. One might worry that one or two groups of responses influence greater than others so that they would bias the resulting averages. To check this conjecture, we leave one question away and take the average of responses from the remaining six questions. Following the construction rule for proxy 4, we construct seven different proxies. Table **??** presents the coefficient estimates. The first column label 'Pro tax' means that the property tax question is left out. Interpretation on the rest of columns follows the first column. Compared to column (4) in Table **??**, we find no notable difference. We try the same robustness checks on all other proxies but find no meaningful difference as well.

Another possible concern would be that we use too small number of questions. Now we add the home value question and the vehicle value question. We rule out them because they are too subjective questions. Unlike checking account, there are no convenient references, and therefore answering detailed number is hardly likely. Table **??** present the result, and the specifications are the same as Table **??**. We find no significant difference.

One might raise the question whether we can find the similar findings when we extend the sample age. Now we include the respondents ages 50 and older and estimate the parameters using the same set of questions as Table **??**. Table **??** presents the results. Note that the signs of age are inconsistent

9. See Table **??** and Table **??**.

among the proxies. It is due to the fact that the cognitive ability does not change much until age 65 (Figure **??**). Hence, it is possibly advisable to use the proxies for the respondents ages 65 and older.

One of the most challenging concern is to deal with the respondent's motivation. According to Krosnick (1991) and Gideon, Helppie-McFall, and Hsu (2017), rounding is more common for respondents who are low in motivation. Thus far, we have not controlled anything related to motivation, and hence our estimates might have an omitted variable bias. Motivation could be manifested in a various form. To mitigate the issue, we try to construct an index as a proxy for motivation. We note that some respondents choose DK dominantly in most questions (Figure 9). It is possible that the respondents overlook the questions and choose DK unconsciously because of low motivation. Here we use the ratio of opt-outs to the total number of responses as a proxy for motivation. That is, the less motivated respondents tend to choose more opt-outs.

We use the all the questions in three sections[10]. We calculate the proportion of opt-outs to all the responses and label it as 'demotivation'. Table **??** presents the individual fixed effects model using each proxy as the dependent variable. As expected, the sign of demotivation is negative and statistically significant. Controlling for the change in age, cognition and other controls, more de motivated respondents tend to round more (or more likely chooses opt-outs). Compared to Table **??**, we find there is no meaningful difference in terms of the magnitude and significance, and hence we conclude that motivation might not be a concern.

6 Future Works: Application to the PSID

The goal of the project is to construct the index from the way people respond to survey questions even when the direct measure of cognition is not available. There are several reasons why we choose PSID as the application. First, it has a panel dimension. Second, it offers the explicit opt-out options DK. Lastly, PSID has the similar set of questions as in the HRS. We examine the latest five waves of data from 2009 to 2017.

The PSID was launched in 1968 by the Institute for Social Research at the University of Michigan.

10. The selected sections are 'Health Care Costs', 'Housing', and 'Assets, Debts, Income'. 7 questions selected for proxies belong to these sections.

It was annually published until 1997, but since then it has been published once in two years. The PSID provides detailed information on assets and liabilities with diverse demographic backgrounds. The PSID respondents consist of three groups: the core sample, low-income-family sample, and immigrant sample. The core sample has the largest proportion of them, and they are sampled from the Survey Research Center (SRC), which are representative of the US population. The initial criteria for sample selection focuses household head sampled from the SRC. We select the respondents ages 65 and older.

The list of questions is property tax, checking account, social security income, doctor visit expenditure and drug expenditure. We construct 7 proxies and standardize them as in the HRS analysis. PSID has richer set of demographics compared to the HRS. Information on race and state-level geocode is available even in public data. The downside of data for our purpose is too few observations on old respondents (about 780 respondents in each wave). Figure 9 presents the local average of proxies by age. It is puzzling that there are opposing trends among the proxies. Figure **??** shows the local average controlling for the individual fixed effects. There is no upper sloping, even though the trends are not as clear as the HRS data in Figure 7.

Next, we examine the correlation between the constructed proxies and the respondents' characteristics. We regress each proxy on age, gender, education, marital status, and wealth quantile[11]. The cross individual analysis presents in Table **??**. Like Figure 9, the resulting coefficients are not consistent among the proxies. Further, the sign on age is not intuitive. Table **??** presents the individual fixed effects model showing more consistent patterns among the proxies. Thus far, it is less clear whether the inconsistent results are due to the data characteristics or the methods. The methods can be tailored to meet data characteristics. Again, the analysis is preliminary, and hence we have not concluded whether our method is applicable to PSID yet.

11. Interview mode is available, but all the respondents in the sample use the phone survey.

Table 1: Descriptive statistics for HRS respondents

survey year	observations	female (%)	age	schooling years	phone interview (%)
2004	7,825	74.8	68.3	12.1	24.2
2006	7,371	75.3	69.6	12.1	41.4
2008	7,030	74.9	70.4	12.2	41.7
2010	8,637	71.9	67.2	12.4	34.9
2012	8,223	71.6	68.2	12.5	41.5
2014	7,750	71.6	69.1	12.5	56.3
2016	8,700	70.3	67.1	12.7	63.3
2018	7,315	70.3	68.3	12.7	56.4

The table summarizes the respondents by the HRS survey wave. The sample is drawn from the Survey Research Center, which is representative of the US population. Also, the sample selection focuses on the household head only.

Table 2: Descriptive statistics for the selected questions

question	observations	average	standard deviation		Opt-out	
				Don't know	Refused to Answer	<10
Home value	36,762	232,432.1	1,044,092.9	15.6	1.2	.2
Property tax	39,971	2,030.6	4,671.5	18.8	1.4	5
SSI income	43,588	1,010.6	583.3	5.8	9	2
Checking	46,287	26,407.4	114,548.5	11	10.5	3.7
Vehicle	45,520	13,841.5	64,626.7	17.7	1.4	2.1
Food home	61,715	92.7	1,429.7	9.9	1	1.8
Food out	61,729	25.2	173.7	3.1	.7	40.2
OOP Doc	33,027	583.6	2,425.9	18.1	.6	5.8
OOP Dent	30,174	1,129	2,184.5	7.5	.5	3.4
OOP Drug	39,925	80.1	341.4	11.8	.4	12.7

The last three columns are the proportions. The last column <10 presents the percent of numerical answers less than 10.
The full question texts are:
Home value: *What is its present value? I mean, what would it bring if it were sold today?*
Property tax: *What were the real estate taxes in (LAST CALENDAR YR CALCULATED) on this home?*
SSI income: *About the Social Security income that you (yourself) receive, how much was that Social Security check, or the amount deposited directly into an account, last month?*
Checking: *If you added up all such accounts, about how much would they amount to right now?*
Vehicle: *What are they worth altogether, minus anything you still owe on them?*
Food home: *How much do you (and other family members living there) spend on food that you use at home in an average week?*
Food out: *bout how much do you spend eating out in a typical week, not counting meals at work or at school?*
OOP Doc: *About how much did you pay out-of-pocket for doctor or clinic visits?*
OOP Dent: *About how much did you pay out-of-pocket for dental bills?*
OOP Drug: *On average, about how much have you paid out-of-pocket per month for these prescriptions?*

Table 3: Regression of the proxies on the selected controls

	(1) proxy 1	(2) proxy 2	(3) proxy 3	(4) proxy 4	(5) proxy 5	(6) proxy 6	(7) proxy 7
age	0.00116	-0.000806	-0.00321***	-0.00942***	-0.00946***	-0.00590***	-0.0132***
	(0.000807)	(0.000810)	(0.000828)	(0.000798)	(0.000770)	(0.000838)	(0.000706)
cognitive score	0.0318***	0.0324***	0.0657***	0.0944***	0.108***	0.134***	0.102***
	(0.00617)	(0.00620)	(0.00633)	(0.00610)	(0.00588)	(0.00640)	(0.00540)
phone interview	-0.0561***	-0.0629***	-0.0488***	-0.0384***	-0.00899	-0.0189*	0.00987
	(0.0103)	(0.0103)	(0.0105)	(0.0101)	(0.00979)	(0.0106)	(0.00898)
education	-0.0241***	-0.0305***	-0.0275***	-0.0316***	-0.0179***	0.00628***	-0.0128***
	(0.00204)	(0.00205)	(0.00209)	(0.00202)	(0.00194)	(0.00211)	(0.00178)
female	0.0876***	0.0941***	0.0732***	0.0403***	-0.0357***	0.109***	-0.0516***
	(0.0116)	(0.0117)	(0.0119)	(0.0115)	(0.0111)	(0.0121)	(0.0102)
wealth quantile	-0.00385***	-0.00647***	-0.00277***	-0.00288***	0.00285***	0.0116***	0.00316***
	(0.000191)	(0.000191)	(0.000196)	(0.000189)	(0.000182)	(0.000198)	(0.000167)
observations	27526	27526	27641	27641	27641	27637	27641
R^2	0.032	0.072	0.024	0.036	0.037	0.178	0.053
F	153.8	355.9	112.3	172.6	174.9	994.4	259.2

Standard errors in parentheses

Estimates are based on Eq. (1) for the HRS sample. All the proxies and the cognitive score are standardized.

* $p < 0.10$, ** $p < .05$, *** $p < .01$

proxy 1: Gideon method with reverse order $\left(\frac{n-1}{m-1}\right)$
proxy 2: $\frac{n}{m}$
proxy 3: Based on proxy 1, assign 0 to DK
proxy 4: Based on proxy 2, assign 0 to DK
proxy 5: assign 0 to DK; 1 to maximal rounding; 2 to other numerical response
proxy 6: assign 0 to DK or maximal rounding; 1 to other numerical response
proxy 7: assign 0 to DK; 1 to other numerical response
n: the number of non-trailing zeros
m: the number of total digits

Table 4: Regression of the cognitive scores on the proxies

	(1)	(2)	(3)
age	-0.0361***	-0.0360***	-0.0339***
	(0.000757)	(0.000757)	(0.000759)
phone interview	0.0155	0.0158	0.0139
	(0.0100)	(0.0100)	(0.00994)
education	0.100***	0.100***	0.0979***
	(0.00190)	(0.00190)	(0.00190)
female	0.285***	0.284***	0.277***
	(0.0112)	(0.0112)	(0.0112)
wealth quantile	0.00647***	0.00655***	0.00504***
	(0.000183)	(0.000186)	(0.000203)
proxy 1	0.0304***		
	(0.00588)		
proxy 2		0.0306***	-0.0000967
		(0.00586)	(0.00617)
proxy 6			0.0866***
			(0.00658)
proxy 7			0.0780***
			(0.00780)
observations	27526	27526	27511
R^2	0.247	0.247	0.260
F	1505.4	1505.6	1209.2

Standard errors in parentheses

All the proxies and the cognitive score are standardized.

* $p < 0.10$, ** $p < .05$, *** $p < .01$

Table 5: Regression of the proxies on the selected controls for the old respondents

	(1) proxy 1	(2) proxy 2	(3) proxy 3	(4) proxy 4	(5) proxy 5	(6) proxy 6	(7) proxy 7
age	-0.00252	-0.00698***	-0.00609***	-0.0131***	-0.00720***	-0.0188***	-0.0119***
	(0.00190)	(0.00188)	(0.00198)	(0.00186)	(0.00185)	(0.00204)	(0.00164)
cognitive score	0.0281**	0.0298***	0.0470***	0.0601***	0.0565***	0.0441***	0.0545***
	(0.0115)	(0.0114)	(0.0117)	(0.0109)	(0.0110)	(0.0113)	(0.00974)
phone interview	-0.0393***	-0.0420***	-0.0321**	-0.0253**	-0.0144	-0.0202*	0.00270
	(0.0130)	(0.0127)	(0.0131)	(0.0120)	(0.0119)	(0.0123)	(0.0106)
wealth quantile	-0.00110**	-0.00257***	0.000499	0.00149***	0.00452***	0.00702***	0.00517***
	(0.000480)	(0.000475)	(0.000478)	(0.000469)	(0.000485)	(0.000494)	(0.000462)
observations	27526	27526	27641	27641	27641	27637	27641
R^2	0.525	0.568	0.530	0.577	0.549	0.652	0.583
F	6.427	16.79	12.42	34.16	39.48	100.1	60.36

Standard errors are clustered at the individual level and are presented in parentheses.
Estimates are based on Eq. (1) for the HRS sample older than 65. All the proxies and the cognitive score are standardized.
Individual fixed effect is included in all estimations.
* $p < 0.10$, ** $p < .05$, *** $p < .01$

proxy 1: Gideon method with reverse order $\left(\frac{n-1}{m-1}\right)$
proxy 2: $\frac{n}{m}$
proxy 3: Based on proxy 1, assign 0 to DK
proxy 4: Based on proxy 2, assign 0 to DK
proxy 5: assign 0 to DK; 1 to maximal rounding; 2 to other numerical response
proxy 6: assign 0 to DK or maximal rounding; 1 to other numerical response
proxy 7: assign 0 to DK; 1 to other numerical response
n: the number of non-trailing zeros
m: the number of total digits

Table 6: Robustness Check I: Regression of the special proxies on the selected controls for the old respondents

	(1) Pro tax	(2) SSI	(3) checking	(4) food at home	(5) OOP doc	(6) OOP dent	(7) OOP drug
age	-0.0131***	-0.0108***	-0.0147***	-0.0118***	-0.0123***	-0.0132***	-0.0118***
	(0.00192)	(0.00200)	(0.00194)	(0.00183)	(0.00185)	(0.00190)	(0.00183)
cognitive score	0.0583***	0.0464***	0.0627***	0.0605***	0.0539***	0.0573***	0.0579***
	(0.0114)	(0.0119)	(0.0113)	(0.0108)	(0.0108)	(0.0111)	(0.0107)
phone interview	-0.0237*	-0.0134	-0.0244*	-0.0238**	-0.0321***	-0.0238*	-0.0267**
	(0.0124)	(0.0132)	(0.0125)	(0.0117)	(0.0119)	(0.0122)	(0.0119)
wealth quantile	0.00152***	0.000736	0.00267***	0.00112**	0.00119**	0.00139***	0.00136***
	(0.000495)	(0.000508)	(0.000480)	(0.000455)	(0.000469)	(0.000480)	(0.000464)
observations	27632	27607	27637	27550	27641	27638	27639
R^2	0.547	0.521	0.575	0.584	0.573	0.567	0.583
F	30.58	17.22	43.31	29.83	30.60	31.95	30.46

The dependent variable in each column is based on the proxy 4, but each column leaves one question away.

The taken-out question is shown in the column label.

Standard errors are clustered at the individual level and are presented in parentheses.

Estimates are based on Eq. (1) for the HRS sample older than 65. All the proxies and the cognitive score are standardized.

Individual fixed effect is included in all estimations.

* $p < 0.10$, ** $p < .05$, *** $p < .01$

Table 7: Robustness Check II: Regression of the special proxies on the selected controls for the old respondents

	(1) proxy 1	(2) proxy 2	(3) proxy 3	(4) proxy 4	(5) proxy 5	(6) proxy 6	(7) proxy 7
age	-0.00225	-0.00506***	-0.00496***	-0.0101***	-0.00789***	-0.0236***	-0.0101***
	(0.00176)	(0.00170)	(0.00186)	(0.00172)	(0.00173)	(0.00190)	(0.00153)
cognitive score	0.0242**	0.0231**	0.0395***	0.0494***	0.0542***	0.0532***	0.0499***
	(0.0107)	(0.0103)	(0.0111)	(0.0100)	(0.0102)	(0.0104)	(0.00899)
phone interview	-0.0423***	-0.0456***	-0.0327***	-0.0226**	-0.00914	-0.0138	0.0110
	(0.0119)	(0.0113)	(0.0123)	(0.0108)	(0.0109)	(0.0110)	(0.00951)
wealth quantile	-0.00112**	-0.00285***	0.000891**	0.00198***	0.00622***	0.00864***	0.00623***
	(0.000449)	(0.000440)	(0.000453)	(0.000435)	(0.000455)	(0.000455)	(0.000424)
observations	27618	27618	27648	27648	27648	27648	27648
R^2	0.541	0.601	0.549	0.606	0.581	0.706	0.607
F	7.356	19.26	11.32	28.80	68.48	175.9	81.83

Two more questions, home and vehicle value, are added on each proxy construction.

Standard errors are clustered at the individual level and are presented in parentheses.

Estimates are based on Eq. (1) for the HRS sample older than 65. All the proxies and the cognitive score are standardized.

Individual fixed effect is included in all estimations.

* $p < 0.10$, ** $p < .05$, *** $p < .01$

Table 8: Robustness Check III: Regression of the proxies on the selected controls

	(1) proxy 1	(2) proxy 2	(3) proxy 3	(4) proxy 4	(5) proxy 5	(6) proxy 6	(7) proxy 7
age	0.00771***	0.00251*	0.00686***	-0.000543	0.00492***	0.00414***	-0.00453***
	(0.00135)	(0.00132)	(0.00143)	(0.00132)	(0.00130)	(0.00152)	(0.00112)
cognitive score	0.0213**	0.0230***	0.0377***	0.0471***	0.0457***	0.0499***	0.0410***
	(0.00869)	(0.00849)	(0.00895)	(0.00815)	(0.00818)	(0.00838)	(0.00710)
phone interview	-0.0331***	-0.0356***	-0.0279***	-0.0223**	-0.0142	-0.0234**	0.00244
	(0.00979)	(0.00946)	(0.0101)	(0.00897)	(0.00907)	(0.00927)	(0.00767)
wealth quantile	-0.000959***	-0.00261***	0.000309	0.000762**	0.00398***	0.00637***	0.00421***
	(0.000364)	(0.000356)	(0.000370)	(0.000347)	(0.000358)	(0.000377)	(0.000325)
observations	46022	46022	46216	46216	46216	46246	46216
R^2	0.514	0.559	0.509	0.544	0.503	0.633	0.546
F	12.27	18.60	10.24	11.92	41.20	83.97	55.43

Standard errors are clustered at the individual level and are presented in parentheses.

Estimates are based on Eq. (1) for the HRS sample. All the proxies and the cognitive score are standardized.

Individual fixed effect is included in all estimations.

* $p < 0.10$, ** $p < .05$, *** $p < .01$

Table 9: Regression of the proxies on the selected controls from PSID

	(1) proxy 1	(2) proxy 2	(3) proxy 3	(4) proxy 4	(5) proxy 5	(6) proxy 6	(7) proxy 7
age	-0.000399	-0.00124	-0.00245	-0.00529***	-0.0115***	-0.0267***	-0.0148***
	(0.00179)	(0.00175)	(0.00178)	(0.00179)	(0.00211)	(0.00144)	(0.00238)
phone interview	0.276***	0.221***	0.312***	0.333***	0.458***	0.161***	0.541***
	(0.0816)	(0.0799)	(0.0788)	(0.0791)	(0.0933)	(0.0623)	(0.106)
education	0.0200***	0.0137***	0.0259***	0.0253***	0.0338***	0.0103***	0.0419***
	(0.00378)	(0.00371)	(0.00376)	(0.00377)	(0.00445)	(0.00308)	(0.00504)
female	0.0604***	0.0777***	0.0435**	0.0440**	-0.0675***	-0.0100	-0.110***
	(0.0209)	(0.0205)	(0.0209)	(0.0210)	(0.0248)	(0.0172)	(0.0281)
wealth quantile	-0.0147***	-0.0209***	-0.0147***	-0.0203***	0.00114**	-0.000794**	-0.000326
	(0.000446)	(0.000437)	(0.000447)	(0.000449)	(0.000529)	(0.000359)	(0.000600)
observations	9857	9857	10114	10114	10114	10496	10114
R^2	0.111	0.216	0.105	0.185	0.018	0.037	0.020
F	245.0	543.0	237.0	460.1	38.09	79.75	40.87

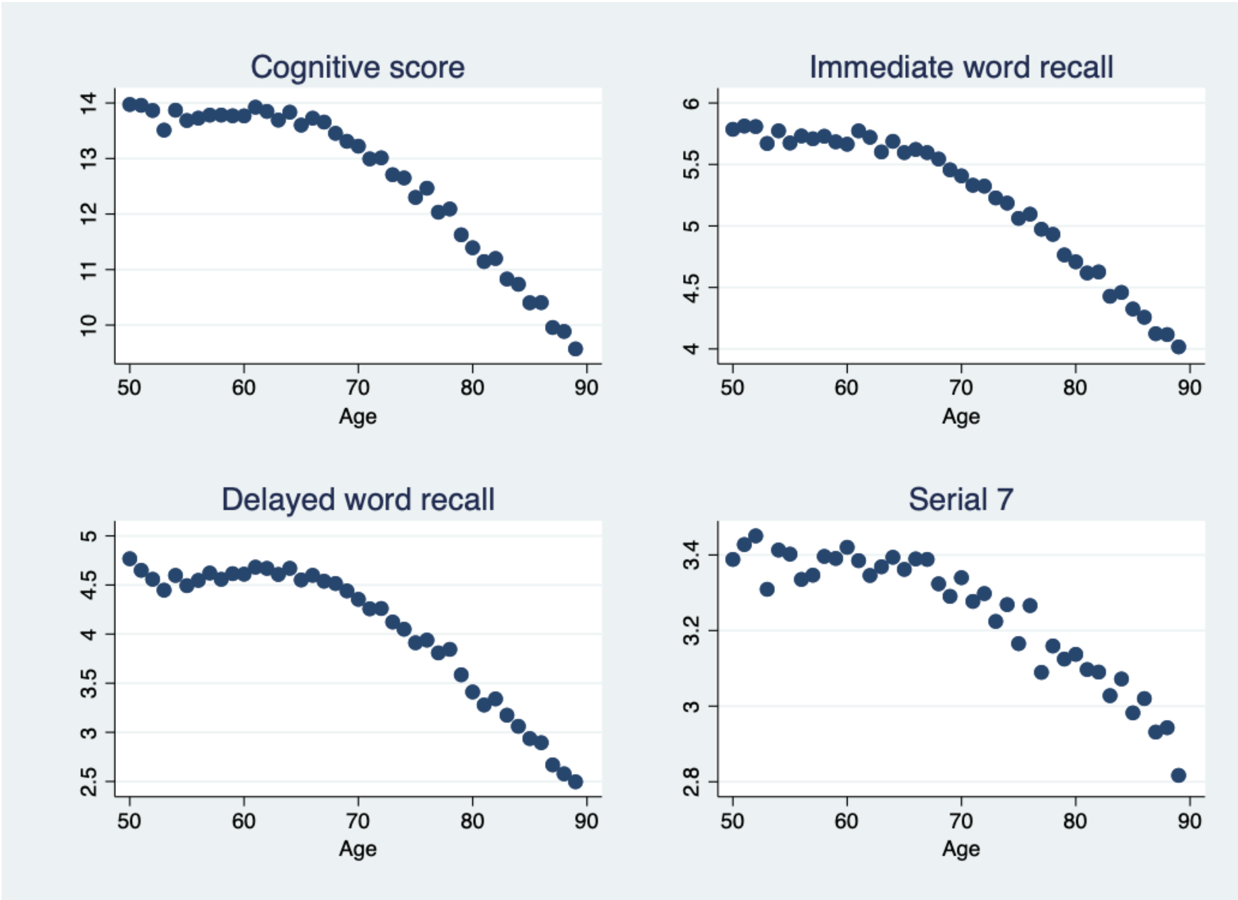
Standard errors are in parentheses, and all the proxies are standardized.

Estimates are based on Eq. (1) for the PSID sample between 65 and 85 years old.

* $p < 0.10$, ** $p < .05$, *** $p < .01$

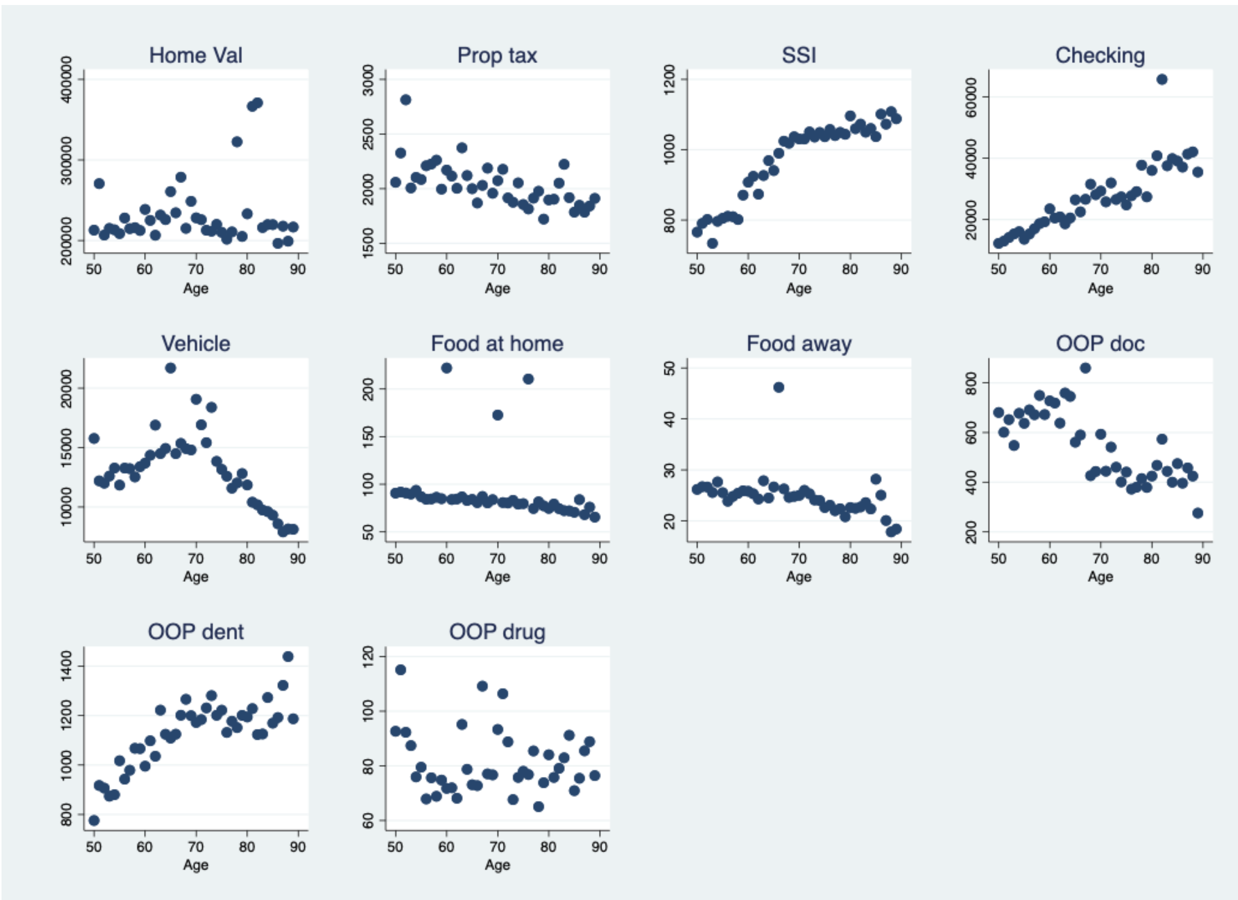
proxy 1: Gideon method with reverse order $\left(\frac{n-1}{m-1}\right)$
proxy 2: $\frac{n}{m}$
proxy 3: Based on proxy 1, assign 0 to DK
proxy 4: Based on proxy 2, assign 0 to DK
proxy 5: assign 0 to DK; 1 to maximal rounding; 2 to other numerical response
proxy 6: assign 0 to DK or maximal rounding; 1 to other numerical response
proxy 7: assign 0 to DK; 1 to other numerical response
n: the number of non-trailing zeros
m: the number of total digits

Figure 1: Age trend of cognitive scores



These figures plot the average score of the cognition-related questions in HRS against age in years. The first panel plots the sum score of the three questions: immediate word recall, delayed word recall, and serial 7's test. The rest of the panel presents the score of each question.

Figure 2: Local average of numerical response



These figures plot the average numerical responses of the selected questions from HRS against age in years.

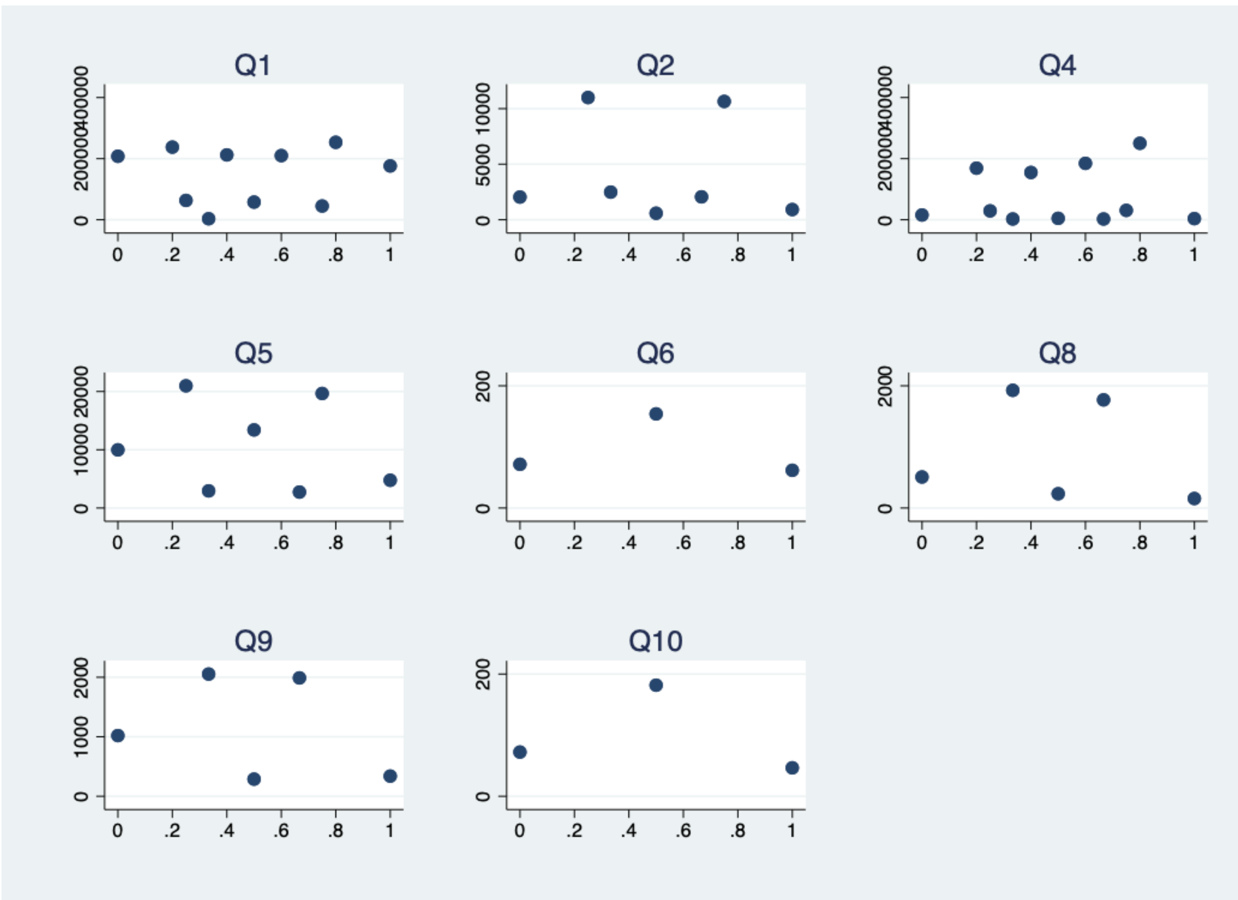
Figure 3: Response heaping

This figure plots the numerical responses of the selected questions from HRS. In each plot, Y-axis represents the frequency of the response.

Figure 4: Distribution of First Index

In X-axis, 0 implies the maximal rounding, and 1 implies there is no trailing zero in the response.

Figure 5: Local Average of numerical response by First Index



In X-axis, 0 implies the maximal rounding, and 1 implies the most detailed numerical response. For this figure, we control for the outlier by removing 99 percentile responses.

Figure 6: Local Average of Proxies by Age

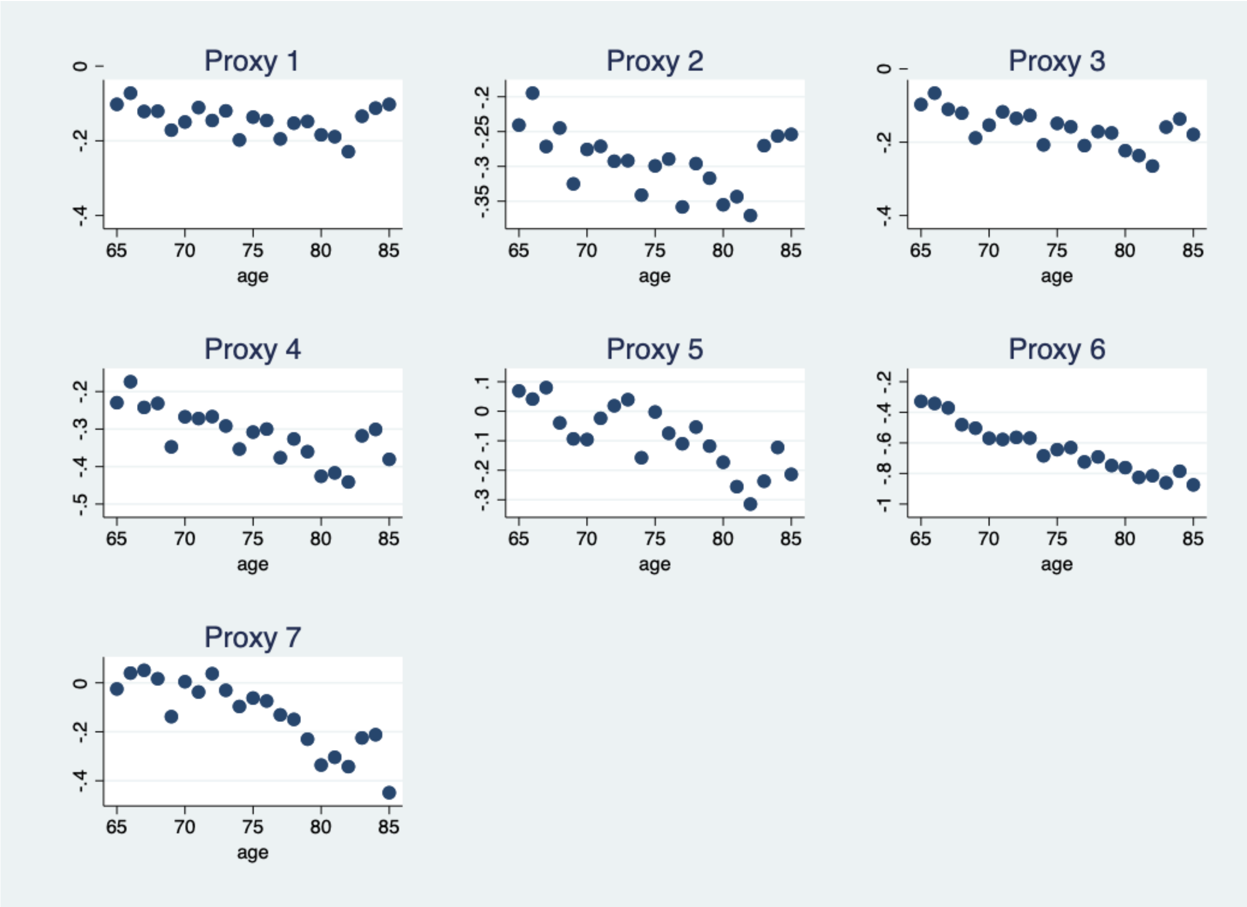
These figures plot the average of the proxies against age in years.

proxy 1: Gideon method with reverse order $\left(\frac{n-1}{m-1}\right)$
proxy 2: $\frac{n}{m}$
proxy 3: Based on proxy 1, assign 0 to DK
proxy 4: Based on proxy 2, assign 0 to DK
proxy 5: assign 0 to DK; 1 to maximal rounding; 2 to other numerical response
proxy 6: assign 0 to DK or maximal rounding; 1 to other numerical response
proxy 7: assign 0 to DK; 1 to other numerical response
n: the number of non-trailing zeros
m: the number of total digits
The cognitive score and all proxies are standardized.

Figure 7: Local Average of Proxies by Age controlling for Individual Effect

The cognitive score and all proxies are standardized. The detail information on proxies are presented in Figure 6.

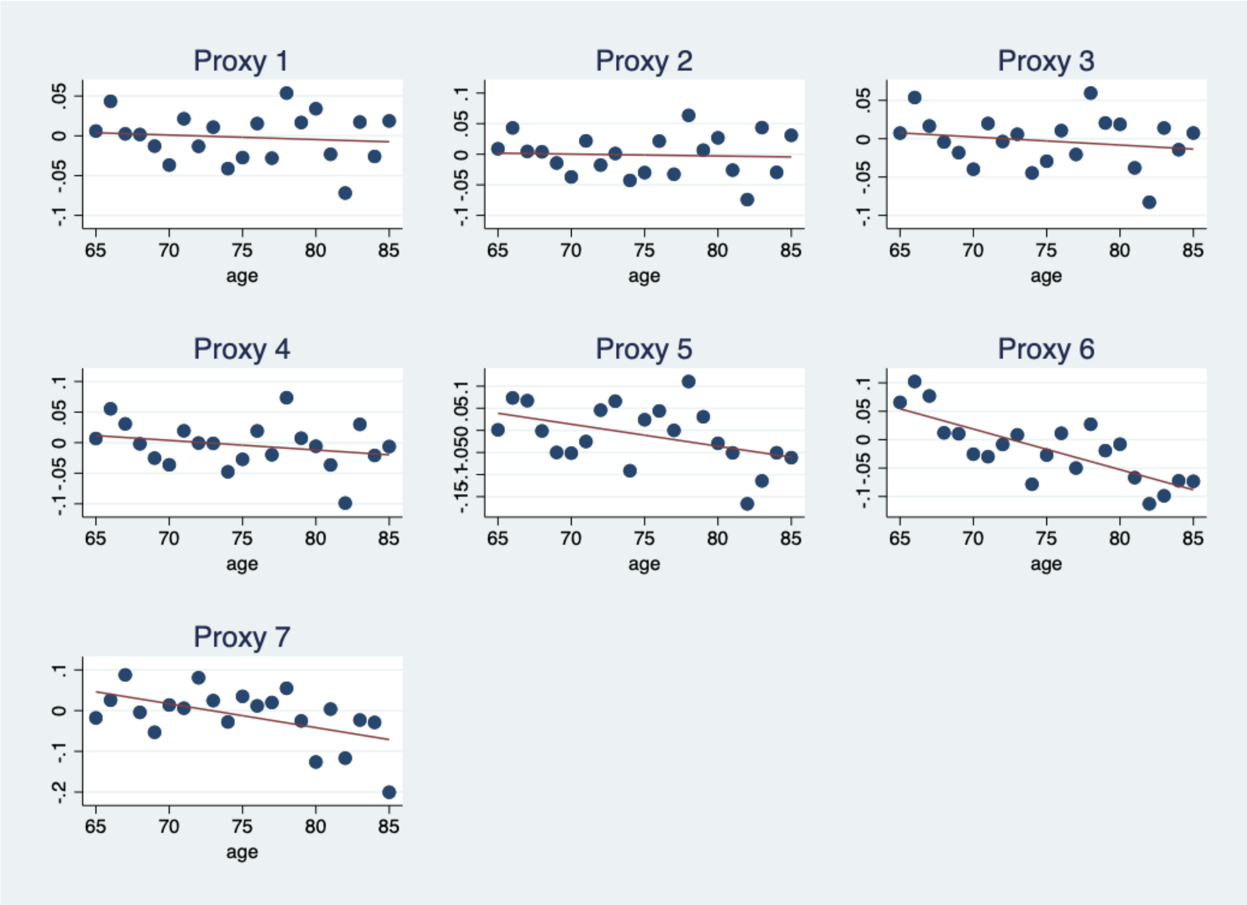
Figure 8: Local Average of Proxies by Age from PSID



These figures plot the average of the proxies against age in years.

proxy 1: Gideon method with reverse order $\binom{n-1}{m-1}$
proxy 2: $\frac{n}{m}$
proxy 3: Based on proxy 1, assign 0 to DK
proxy 4: Based on proxy 2, assign 0 to DK
proxy 5: assign 0 to DK; 1 to maximal rounding; 2 to other numerical response
proxy 6: assign 0 to DK or maximal rounding; 1 to other numerical response
proxy 7: assign 0 to DK; 1 to other numerical response
n: the number of non-trailing zeros
m: the number of total digits
The proxies are standardized.

Figure 9: Local Average of Proxies by Age controlling for Individual Effect from PSID



The proxies are standardized. The detail information on proxies are presented in Figure 8.

I tested whether Title VI of the 1964 Civil Rights Act would have changed black people's cognitive development. The idea is based on the fact that the widespread racial segregation in medical access before the act caused black women to have worse prenatal care. The act transformed their medical access for the black mother so that those born after the act would have better cognitive development.

I select the sample born between 1962 and 1967.

Year	Total	Black (%)	South (%)	South and Black (%)
1962	269	40.5	41.6	72.3
1963	278	38.8	42.8	67.2
1964	263	41.4	41.8	73.6
1965	226	40.3	44.2	70.0
1966	220	38.2	45.9	66.3
1967	216	36.6	46.8	52.5

Then I test the following specification

$$y_{ist} = \alpha + \gamma Black_i + \gamma d_t + \beta \left(Black_i \cdot d_t \right) + \delta X_i + \epsilon_t + \epsilon_s + \epsilon_{ist}$$

Let $Black_i$ be a dummy for black respondent and d_t be a time dummy that switches on for individuals born after 1965 (after the Title VI). X_i includes whether one is born in Southern state, have a phone interview, years of education, age and wealth quantile. I employ survey year fixed effects ϵ_t and grow-up state fixed effects ϵ_s (s indicates what state the individual i grow up). Standard errors are clustered at individual level. My hypothesis is $\beta > 0$

Table 10: Trends in cognitive scores for born between 1962 and 1967

	(1) proxy 1	(2) proxy 2	(3) proxy 3	(4) proxy 4	(5) proxy 5	(6) proxy 6	(7) proxy 7
age	0.0771	0.139	0.103	0.173	0.0229	-0.0567	0.106
	(0.133)	(0.133)	(0.134)	(0.132)	(0.116)	(0.125)	(0.0921)
civil right act (d_t)	-0.00794	0.0201	0.00163	0.0328	-0.0622	-0.0599	0.0378
	(0.0681)	(0.0686)	(0.0686)	(0.0681)	(0.0627)	(0.0673)	(0.0477)
black	-0.0741	0.0522	-0.115**	-0.0218	-0.364***	-0.182***	-0.216***
	(0.0577)	(0.0571)	(0.0574)	(0.0558)	(0.0507)	(0.0549)	(0.0412)
civil right act × black	0.144**	0.104	0.157**	0.118*	0.199***	0.173***	0.0395
	(0.0691)	(0.0685)	(0.0694)	(0.0681)	(0.0618)	(0.0647)	(0.0501)
south	-0.0197	-0.0209	-0.0323	-0.0479	-0.00800	-0.0672	-0.0938*
	(0.0719)	(0.0707)	(0.0734)	(0.0710)	(0.0809)	(0.0783)	(0.0547)
phone	0.130	0.0866	0.123	0.0901	0.173**	0.0827	0.0493
	(0.104)	(0.0956)	(0.104)	(0.0961)	(0.0840)	(0.0783)	(0.0907)
education	0.00906	-0.0120	0.0111	-0.00728	0.0420***	0.0320***	0.0165***
	(0.00853)	(0.00928)	(0.00852)	(0.00892)	(0.00752)	(0.00820)	(0.00472)
wealth	-0.00751***	-0.0124***	-0.00761***	-0.0122***	0.00218***	0.000513	-0.000822*
	(0.000588)	(0.000627)	(0.000588)	(0.000611)	(0.000525)	(0.000558)	(0.000457)
N	8783	8783	8828	8828	8828	8991	8828
R^2	0.064	0.161	0.063	0.146	0.066	0.032	0.025
F	22.86	70.28	22.84	66.05	20.56	5.155	6.115

Standard errors in parentheses

* $p < 0.10$, ** $p < .05$, *** $p < .01$

proxy 1: Gideon method with reverse order $\left(\frac{n-1}{m-1}\right)$

proxy 2: $\frac{n}{m}$

proxy 3: Based on proxy 1, assign 0 to DK

proxy 4: Based on proxy 2, assign 0 to DK

proxy 5: assign 0 to DK; 1 to maximal rounding; 2 to other numerical response

proxy 6: assign 0 to DK or maximal rounding; 1 to other numerical response

proxy 7: assign 0 to DK; 1 to other numerical response

n: the number of non-trailing zeros

m: the number of total digits

Table 11: Trends in cognitive scores for full sample

	(1) proxy 1	(2) proxy 2	(3) proxy 3	(4) proxy 4	(5) proxy 5	(6) proxy 6	(7) proxy 7
age	-0.00423	-0.0301***	-0.0167*	-0.0542***	-0.0736***	-0.274***	-0.0882***
	(0.0101)	(0.0100)	(0.0101)	(0.0102)	(0.0101)	(0.00916)	(0.0118)
civil right act (d_t)	-0.0454**	-0.0817***	-0.0681***	-0.125***	-0.0728***	-0.140***	-0.157***
	(0.0192)	(0.0193)	(0.0193)	(0.0195)	(0.0188)	(0.0188)	(0.0191)
black	0.0215	0.0868***	-0.0120	0.0190	-0.203***	-0.0323*	-0.212***
	(0.0219)	(0.0220)	(0.0220)	(0.0224)	(0.0209)	(0.0191)	(0.0250)
civil right act $\times$ black	0.00641	0.0590***	0.0144	0.0761***	-0.0316	0.00406	0.0809***
	(0.0221)	(0.0221)	(0.0221)	(0.0224)	(0.0214)	(0.0205)	(0.0247)
south	-0.0234	-0.0456**	-0.0382*	-0.0723***	-0.0208	-0.0681***	-0.0845***
	(0.0197)	(0.0191)	(0.0201)	(0.0200)	(0.0202)	(0.0191)	(0.0250)
phone	0.0997***	0.0801***	0.106***	0.101***	0.116***	0.00693	0.0959***
	(0.0222)	(0.0206)	(0.0222)	(0.0221)	(0.0252)	(0.0236)	(0.0354)
education	0.00721***	-0.0151***	0.0122***	-0.00472**	0.0523***	0.0343***	0.0306***
	(0.00218)	(0.00222)	(0.00219)	(0.00225)	(0.00221)	(0.00210)	(0.00243)
wealth	-0.00797***	-0.0126***	-0.00806***	-0.0124***	0.00152***	-0.000643***	-0.000859***
	(0.000171)	(0.000173)	(0.000173)	(0.000175)	(0.000163)	(0.000162)	(0.000167)
N	101971	101971	103016	103016	103016	104894	103016
R^2	0.055	0.162	0.053	0.142	0.048	0.054	0.021
F	365.4	1065.8	364.0	978.5	176.3	300.7	37.80

Standard errors in parentheses

* $p < 0.10$, ** $p < .05$, *** $p < .01$

proxy 1: Gideon method with reverse order $\left(\frac{n-1}{m-1}\right)$
proxy 2: $\frac{n}{m}$
proxy 3: Based on proxy 1, assign 0 to DK
proxy 4: Based on proxy 2, assign 0 to DK
proxy 5: assign 0 to DK; 1 to maximal rounding; 2 to other numerical response
proxy 6: assign 0 to DK or maximal rounding; 1 to other numerical response
proxy 7: assign 0 to DK; 1 to other numerical response
n: the number of non-trailing zeros
m: the number of total digits

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